Analyzing Strawberry Pricing Strategies Across Canadian Vendors*

Price Variations Driven by Supplier Strategies and Seasonal Demand in Canadian Grocery Markets

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November 25, 2024

This study investigates the pricing of strawberries across eight major suppliers in Canada: Voila, T&T, Loblaws, No Frills, Metro, Galleria, Walmart, and Save-On-Foods. Using a dataset containing variables such as current price, old price, and month, a Bayesian regression model was applied to analyze the relationships between pricing strategies, seasonal trends, and vendor-specific practices. Results reveal significant price variation among suppliers, with old price showing a strong positive correlation with current price, reflecting the impact of prior pricing strategies on current prices. Seasonal trends captured by the month variable indicate subtle but consistent fluctuations in pricing, highlighting the influence of supply and demand dynamics. These findings provide actionable insights into supplier-specific pricing strategies and market behavior, offering valuable guidance to consumers and stakeholders in the Canadian strawberry market.

1 Introduction

Strawberries are one of the most important small berries in Canada and the United States(Macoun and McCubbin (1919)), and pricing of strawberries in the Canadian retail market varies widely due to factors such as supplier strategies, promotional practices, and temporal trends. This investigation examines the determinants of strawberry prices, focusing on differences between different suppliers, the role of discounts, and seasonal effects. By utilizing a Bayesian linear regression model, the study examines the relationship between key predictors (supplier, original price, promotion, and time) and the current price of strawberries. The Bayesian approach not only provides parameter estimates but also quantifies uncertainty,

*Code and data are available at: https://github.com/HeTianning/The-price-of-strawberries thus providing a nuanced understanding of price dynamics in competitive and seasonal markets.

The main objective of this analysis is to estimate and explain the factors that influence retail strawberry prices in Canada. The dependent variable current price reflects the Canadian dollar price per pound of strawberries. The key predictors include supplier identity (categorical), which captures supplier-specific pricing strategies; old price (continuous), which represents the original price before promotion, and month (continuous), which captures temporal or seasonal trends(Hodgdon et al. (2024)). By modeling these relationships, the study aims to quantify how these variables affect pricing and explore their combined impact on strawberry price changes.

The results show significant differences in supplier-specific pricing strategies, with Metro offering higher prices than other suppliers, consistent with its premium market positioning. Time trends indicate a gradual but consistent increase in strawberry prices over time, possibly reflecting seasonal demand or inflationary pressures. Furthermore, the analysis shows a strong relationship between original and discounted prices, suggesting that promotional pricing generally preserves relative price hierarchies among suppliers. Bayesian models confirm strong convergence and robust posterior estimates, ensuring the reliability of these findings.

Understanding the factors driving strawberry prices is critical for both consumers and retailers. For suppliers, insights into pricing dynamics can inform strategies to optimize revenue while remaining competitive. For consumers, this analysis provides valuable information to navigate the market, highlighting opportunities to save costs by selecting suppliers or purchasing during promotions. More broadly, these findings contribute to the study of the fresh produce market, where pricing is influenced by a complex interaction between supplier strategies, seasonal supply, and consumer behavior. This study lays the foundation for future research that could incorporate additional factors, such as geographic differences or organic certification, to further enrich our understanding of pricing dynamics in Canadian retail.

The rest of the paper is structured as follows. Section 2 describes the data collection process, including data sources, sampling strategy, and preprocessing steps taken to ensure data quality. Section 3 outlines the methodological framework, focusing on the Bayesian linear regression model, its formulation, and diagnostic checks. Section 4 presents the main findings of the analysis, focusing on specific supplier pricing strategies, seasonal trends, and the impact of sales and promotions on strawberry prices. Section 5 discusses the implications of these findings, placing them in the broader context of consumer behavior and supplier strategies in the fresh produce market.

2 Data

To conduct the analysis, `R`, a versatile statistical programming language, was utilized for simulating, testing, downloading, cleaning, and modeling data (R Core Team 2023). Several powerful libraries supported various stages of the analysis. The `tidyverse` package suite (Wickham et al. 2019), which includes `dplyr` for data manipulation and `ggplot2` for visualization, was central to handling and exploring the dataset. Data cleaning and structuring were enhanced using `janitor`, while `arrow` facilitated efficient handling of large datasets by enabling seamless reading and writing of data (Apache Arrow 2021). The `here` package streamlined file management, ensuring robust and reproducible workflows (Müller 2020).

Visualization and reporting were further supported by `knitr` (Xie 2021), which enabled dynamic report generation, and `modelsummary` (Arel-Bundock 2022), which provided professional-quality summaries for statistical models. Bayesian modeling and advanced statistical analysis were conducted using `rstanarm` (Goodrich et al. 2022), while posterior diagnostics and visualizations were enhanced with `bayesplot` (Gelman, Gabry, et al. 2021). Testing and quality assurance of code were carried out with `testthat` (Wickham 2011), ensuring the reliability and reproducibility of results.

By integrating these libraries the analysis leveraged a comprehensive ecosystem of tools, demonstrating the strength and flexibility of R in handling complex data-driven research workflows.

2.1 Overview

The data for this analysis was provided by Project Hammer (Filipp 2024), which was collected through a process of scraping website UI screens from vendors within the Toronto community. It contains data on product details (e.g., product name, brand, current and old price, and unit of product) for 8 different grocery stores (Voila, T&T, Loblaws, No Frills, Metro, Galleria, Walmart Canada, and Save-On-Foods). Project Hammer's data is available from February 28, 2024, and since the data is collected by extracting information from grocery store websites, there may be missing data, as discussed in appendix. Through the method of screen scraping, the raw data is intended to measure and reflect grocery store vendor decisions and product pricing trends.

For this analysis, the eight vendors - Voila, T&T, Loblaws, No Frills, Metro, Galleria, Walmart Canada, and Save-On-Foods - and their pricing for strawberries were considered. The variable "price" for each supplier in this analysis reflects the current price of their product at the time the data was downloaded.

2.2 Measurement

The dataset provides a detailed and structured framework for analyzing strawberry pricing dynamics in the Canadian market, offering critical insights into supplier-specific pricing strategies and seasonal trends. The central variable of interest is the current price, a continuous measure representing the price of strawberries in Canadian dollars at the time of observation.

This variable acts as the dependent variable in the analysis and reflects real-time vendor pricing decisions, including adjustments for promotions, sales, or other market-driven factors. The current price is essential for understanding how vendors position their products in response to competition and consumer demand.

Complementing this, the dataset includes the old price, another continuous variable that captures the price of strawberries before any discounts or promotional offers. The old price serves as a benchmark for evaluating vendor markdowns, sales strategies, and pricing flexibility. By calculating the difference between the old price and the current price, the analysis can quantify the extent and frequency of price reductions, revealing patterns in promotional behavior. For instance, larger discounts may indicate aggressive marketing tactics during periods of high supply or low demand. Together, current and old prices allow for a nuanced exploration of how pricing evolves over time and in response to market conditions.

The dataset also incorporates vendor as a categorical variable, identifying one of eight major suppliers: Voila, T&T, Loblaws, No Frills, Metro, Galleria, Walmart, and Save-On-Foods. This variable is pivotal for inter-vendor comparisons, enabling the analysis to uncover unique pricing strategies, competitive behaviors, and market segmentation. By examining differences in pricing across these suppliers, the analysis can identify which vendors consistently offer lower prices, adopt aggressive discounting practices, or align their pricing with premium branding.

Another critical variable is month, recorded as a numeric measure that captures the time of observation on a monthly scale. This variable facilitates the investigation of seasonal trends, allowing for the analysis of how strawberry prices fluctuate throughout the year. Seasonal dynamics may reflect changes in supply (e.g., peak harvest periods), demand (e.g., holidays or special occasions), and vendor-specific pricing adjustments. By integrating month with pricing data, the analysis can identify whether prices tend to peak or dip during specific times of the year and how these patterns vary among vendors.

These variables collectively provide a rich dataset for conducting both granular and aggregate analyses of strawberry pricing. The inclusion of current and old prices enables an in-depth exploration of vendor-specific pricing adjustments, while the categorical vendor variable allows for competitive benchmarking across suppliers. The month variable introduces a temporal dimension, facilitating the study of seasonal effects on pricing. Together, this dataset offers a comprehensive foundation for understanding the complex interplay between market forces, supplier behavior, and seasonal trends, yielding actionable insights for consumers seeking the best value and suppliers aiming to optimize their pricing strategies.

2.3 Outcome variable

The primary outcome variable in this study is current price, which represents the current price of strawberries in Canadian dollars. This continuous variable serves as the dependent variable and captures the prices consumers pay at the point of purchase, reflecting vendor-specific pricing strategies and promotional adjustments. Additionally, old price is included as a secondary outcome variable, representing the original price before any discounts. The relationship between these two variables highlights the frequency and magnitude of price reductions, offering insights into vendor markdown strategies.

The analysis focuses on understanding how current price varies with factors such as vendor and month. The categorical variable vendor identifies the supplier and captures differences in pricing strategies across eight vendors, ranging from premium to budget-focused retailers. These variations help reveal how suppliers target different market segments through pricing. The numeric variable month enables the exploration of seasonal trends and temporal fluctuations, reflecting how supply and demand dynamics influence pricing throughout the year.

By examining both current price and old price, the study provides a detailed view of promotional activity and vendor behavior. A significant gap between the two prices indicates aggressive promotional strategies, while minimal differences suggest stable pricing policies. Additionally, incorporating the month variable allows for insights into seasonal peaks or dips in strawberry prices, such as higher prices during off-seasons or lower prices during harvest months. Together, these variables offer a comprehensive understanding of strawberry pricing dynamics in Canada's retail market, helping inform consumer choices and vendor pricing strategies.

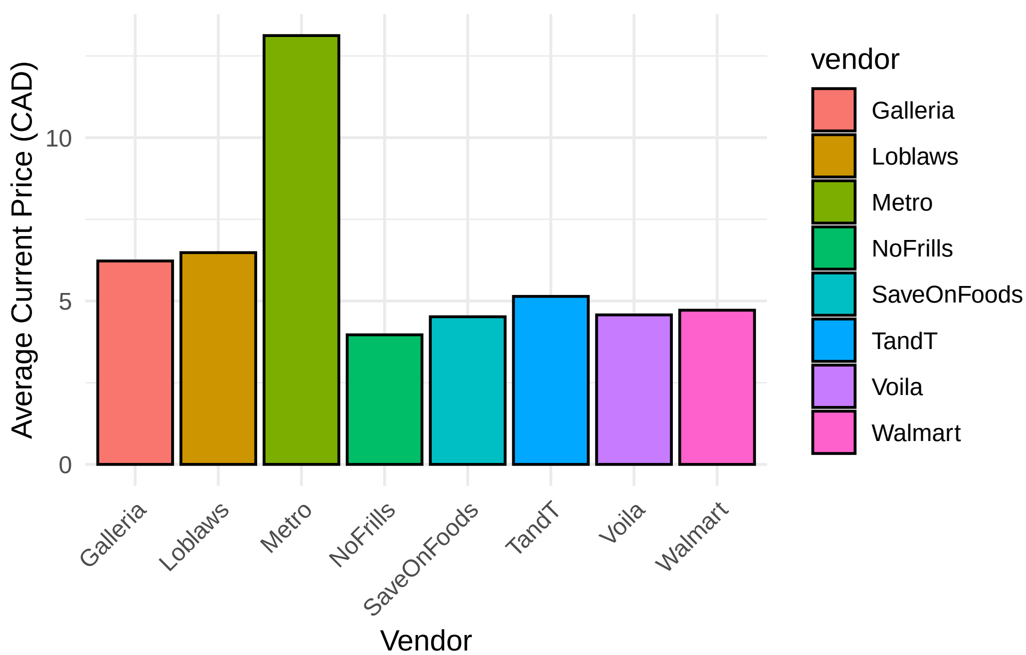


Figure 1: Average Current Price by Vendor

The graph(Figure 1) illustrates the average current price of strawberries across various vendors, highlighting significant price variations. `Metro` stands out with the highest average price, indicating a focus on premium offerings or higher-quality products, while `No Frills` and

`Save-On-Foods` have the lowest prices, appealing to cost-conscious shoppers. Vendors like `Loblaws`, `T&T`, and `Voila` fall into the mid-range pricing category, suggesting a balance between affordability and quality. These differences reflect distinct market strategies, with premium vendors targeting quality-focused consumers and budget-friendly vendors catering to price-sensitive customers. The data provides valuable insights for consumers to make informed purchasing decisions and for vendors to refine their pricing strategies to better compete in their respective market segments.

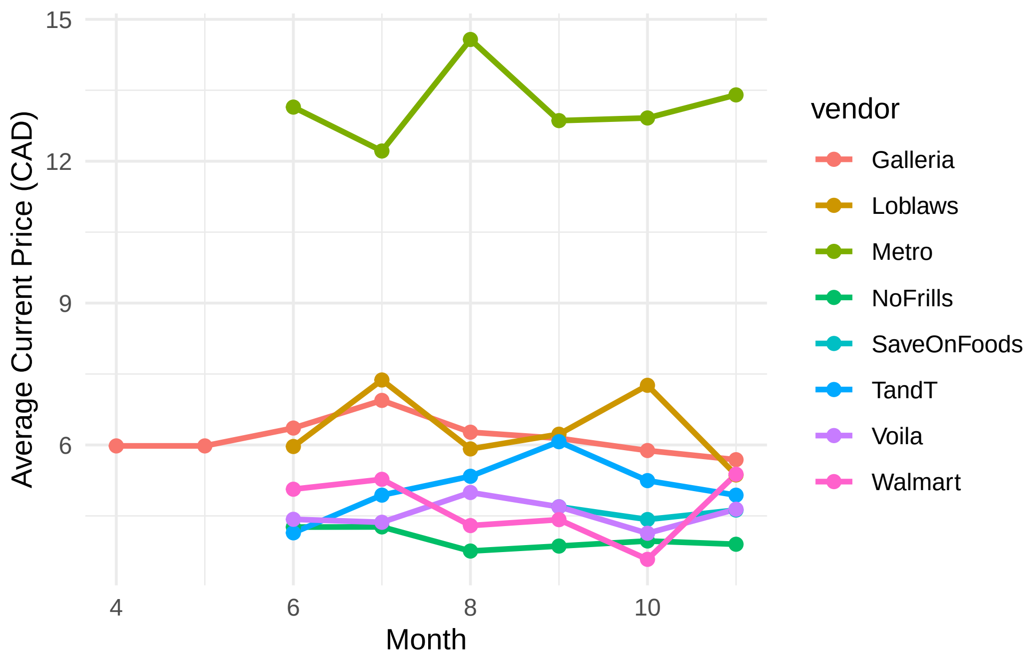


Figure 2: Monthly Trend of Current Prices by Vendor

This graph(Figure 2) shows the monthly trend of average current strawberry prices across different vendors over several months. `Metro` consistently exhibits the highest prices, with noticeable fluctuations, peaking in mid-year, indicating potential seasonal effects or changes in supply and demand. In contrast, budget-friendly vendors like `No Frills` and `Save-On-Foods` maintain the lowest prices, demonstrating pricing stability aimed at cost-conscious consumers. Mid-range vendors such as `Loblaws`, `T&T`, and `Voila` show relatively stable but slightly variable trends, with occasional peaks suggesting targeted pricing adjustments. Overall, the graph highlights clear segmentation among vendors, with premium vendors like `Metro` adapting dynamically to market conditions, while budget vendors maintain consistent affordability. This trend could reflect differing business strategies to cater to diverse consumer preferences.

2.4 Predictor variables

Predictor Variables: Exploring Factors Influencing Strawberry Prices

1. Vendor

The vendor variable is categorical, identifying the supplier of strawberries. Each vendor employs unique pricing strategies, leading to significant variability in pricing across the eight vendors (Voila, T&T, Loblaws, No Frills, Metro, Galleria, Walmart, and Save-On-Foods). Premium vendors like Metro and Galleria tend to target quality-conscious consumers, reflected in their higher average prices. In contrast, budget-oriented vendors like No Frills and Save-On-Foods maintain lower prices to attract cost-sensitive shoppers. The variability in pricing, shown through boxplots, highlights how vendor identity influences price distributions and captures the strategic segmentation of the Canadian strawberry market.

2. Old and Current Prices

The dataset includes two continuous price variables: old price (original price) and current price (price after any promotions or discounts). The difference between these two variables provides insights into promotional behavior and markdown strategies. Vendors like No Frills and Save-On-Foods typically show small gaps between old price and current price, suggesting limited use of deep discounts, whereas Metro and Walmart exhibit larger gaps, reflecting more aggressive promotional activity. Boxplots comparing old price and current price by vendor demonstrate how discounts influence consumer pricing perceptions and vendor competition.

3. Month (month)

The month variable is numeric, capturing the month of observation. Seasonal patterns play a crucial role in strawberry pricing, with supply and demand fluctuations driving price variability. For instance, prices may drop during peak harvest months and increase during off-season periods when strawberries are scarce. Line charts tracking average monthly prices show clear temporal trends, with peaks and dips aligning with these seasonal dynamics. By analyzing month in combination with other predictors, this variable helps uncover how vendors adjust pricing strategies to reflect seasonal demand and supply conditions.

The interplay of vendor, old price, current price, and month allows for a more comprehensive analysis of pricing strategies. For example, vendors like Metro may use larger discounts (old price vs. current price) during peak seasons to maintain competitiveness, while budget vendors like No Frills may maintain consistent pricing throughout the year. A combined analysis using bar charts and line plots highlights how vendor strategies vary with time, providing insights into the dynamic nature of strawberry pricing.

The inclusion of variables like vendor, old price, current price, and month enriches the analysis by offering multiple perspectives on pricing strategies. Vendor captures the segmentation of suppliers into premium and budget categories, reflecting strategic decisions about market positioning. The dual price variables (old price and current price) allow for a deeper understanding of promotional activity and highlight the extent to which vendors rely on discounts to influence consumer behavior.

The addition of month introduces a temporal dimension, enabling the analysis of seasonal trends that are common in agricultural markets. Combining these predictors provides a holistic view of pricing dynamics, revealing how vendors adapt to seasonal supply fluctuations, consumer demand, and competitive pressures.

By leveraging these predictor variables, the study offers actionable insights into how strawberry prices are shaped by market forces, vendor decisions, and seasonal trends. These findings are crucial for both consumers seeking to optimize purchases and vendors aiming to refine their pricing strategies to remain competitive.

3 Model

3.1 Purpose of the Model

The purpose of this model is to identify and quantify the factors influencing the current price of strawberries across various vendors in Canada. The analysis evaluates how key predictors, such as vendor, original price, month, and their interactions, affect pricing. Specifically, the model aims to:

- Quantify the impact of each predictor (e.g., vendor, original price, and month) on strawberry prices.
- Analyze how the gap between original (`old_price`) and discounted (`current_price`) prices varies across vendors.
- Examine seasonal trends in strawberry prices to identify periods of high or low prices.
- Provide actionable insights into vendor pricing strategies and market dynamics.

3.2 Model Description

The chosen model is a **Bayesian linear regression model**, which builds on the simplicity of traditional linear regression while incorporating the Bayesian framework. This allows for probabilistic insights and robust uncertainty quantification, making it well-suited for analyzing the factors driving strawberry prices. Further background details and diagnostics are included in Appendix .4.

Predictors in the Model

- **Vendor (vendor)**: A categorical variable identifying the supplier of strawberries. Different vendors adopt distinct pricing strategies that influence strawberry prices.

- **Original Price (old_price)**: A continuous variable representing the original price of strawberries before discounts or promotions. This variable reflects vendor-specific baseline pricing strategies.
- **Month (month)**: A numeric variable capturing the observation month, enabling the analysis of seasonal trends and time-based fluctuations.
- **Price Gap (old_price − current_price)**: A derived variable quantifying the magnitude of discounts or markdowns applied by vendors.

Model Set-Up

The Bayesian linear regression model is expressed as:

[y_i = *0 +* {vendor[i]} + *{old_price}* *x*{old_price[i]} + *{month}* *x*{month[i]} + _i]

where

- y_i: Current price (current_price) of strawberries for observation i (dependent variable).
- β_0: Intercept, representing the baseline price (reference vendor, average original price, and earliest month).
- $\beta_{\text{vendor}[i]}$: Vendor-specific effect, capturing how each supplier's prices deviate from the baseline vendor.
- $\beta_{\text{old\_price}}$: Effect of the original price, representing how the initial pricing influences the current price.
- β_{month}: Effect of the observation month, capturing seasonal or temporal trends in strawberry pricing.
- ϵ_i: Residual error, accounting for variability not explained by the predictors.

Priors in the Bayesian Framework

For the coefficients (β):

[Normal(0, 2.5)]

For the residual standard deviation (σ):

[Exponential(1)]

The priors in this analysis reflect reasonable assumptions about the relationships between predictors and strawberry prices. Coefficients (β) are assigned normal priors ($\text{Normal}(0, 2.5)$) to reflect the expectation that most effects are small and centered around zero, with moderate variability. For example, $\beta_{\text{old\_price}}$ is expected to be positive, reflecting the influence of original prices on current prices, while β_{month} accounts for typically small seasonal pricing effects. The intercept (β_0) also follows a Normal$(0, 2.5)$, assuming the baseline price is near zero with moderate deviations. Finally, the residual standard deviation (σ) is given an exponential prior (Exponential(1)) to ensure positivity and account for variability not captured by the predictors.

We run the model in R (R Core Team 2023) using the `rstanarm` package of Goodrich et al. (2022). We use the default priors from `rstanarm`.

3.3 Model justification

A Bayesian linear regression model is a suitable approach for this analysis because it balances simplicity, interpretability, and flexibility while quantifying uncertainty in parameter estimates. This model is particularly effective for exploring the continuous outcome variable, current_price, and its relationship with predictors such as vendor, month, and original price (old price). Unlike traditional linear regression, which assumes a deterministic relationship between predictors and the outcome, the Bayesian framework provides posterior distributions for all parameters, enabling richer and more nuanced inferences. This approach allows us to incorporate prior knowledge, account for uncertainty, and provide probabilistic insights into strawberry pricing.

The Bayesian framework also handles sparse or imbalanced data effectively by leveraging prior distributions to stabilize parameter estimates. For example, when certain vendors have fewer observations, the priors prevent overfitting and provide regularized estimates, making the model robust to variability in data distribution. This ensures reliable insights into vendor-specific pricing strategies, seasonal trends, and the influence of baseline (old price) on observed (current price) prices.

Benefits of Using Bayesian Regression:

1. **Uncertainty Quantification**:
    - The Bayesian approach provides posterior distributions for each parameter, allowing for uncertainty quantification. For example, the posterior distribution of β_{vendor} helps quantify the uncertainty around vendor-specific pricing effects.
2. **Incorporating Prior Knowledge**:
    - Priors enable the incorporation of domain knowledge into the analysis. For instance:
        - β_{vendor}: Reflects the expectation that most vendor effects are close to zero, with some deviations.
        - β_{month}: Captures small but meaningful seasonal effects.
        - $\beta_{\text{old\_price}}$: Represents the assumption that higher original prices lead to higher observed prices.

3. **Handling Sparse Data**:

    - Bayesian models stabilize estimates when some categories (e.g., certain vendors) have fewer observations. Priors regularize the estimates, reducing the risk of overfitting.

4. **Probabilistic Insights**:

    - Posterior distributions provide credible intervals, making it easier to interpret parameter estimates. For instance, a 95% credible interval for $\beta_{\text{old\_price}}$ of $[0.8, 1.2]$ means there is a 95% probability that the original price effect lies within this range.

3.4 Choice of Predictors

1. Vendor

- **Role**: The vendor variable is categorical, capturing supplier-specific pricing strategies. Each vendor adopts distinct pricing approaches based on branding, market positioning, and target demographics.
- **Importance**: By including this variable, the model quantifies how much each vendor's prices deviate from the baseline vendor, providing insights into vendor-specific strategies and market segmentation.

2. Month

- **Role**: The numeric `month` variable captures seasonal trends in strawberry pricing. This allows the model to account for temporal effects, such as higher prices during off-seasons or lower prices during harvest periods.
- **Importance**: Including `month` helps the model identify recurring seasonal patterns, enabling a better understanding of time-based price fluctuations.

3. Original Price

- **Role**: The continuous variable `old_price` represents the baseline price before any discounts or promotions. This predictor captures the relationship between promotional activity and observed prices.
- **Importance**: Including this variable enables the model to assess how the gap between `old_price` and `current_price` varies across vendors and time, providing insights into promotional strategies and pricing adjustments.

The Bayesian linear regression model is particularly suited for analyzing strawberry pricing as it allows for robust, interpretable, and probabilistic inferences. By including predictors such as vendor, month, and original price, the model captures vendor-specific pricing strategies, seasonal trends, and promotional behaviors. The chosen priors reflect realistic expectations about the predictors' effects, ensuring the model's estimates are stable and reliable. This approach provides a comprehensive framework for understanding strawberry pricing dynamics in the Canadian market.

4 Results

Our results are summarized in Table **??**.

The Bayesian linear regression model provides valuable insights into the factors affecting strawberry prices (current_price) across Canadian vendors. The results reveal significant differences in vendor pricing strategies, seasonal trends, and the relationship between original and current prices. The intercept ($\beta_0 = 1.52$, SE = 0.66) represents the baseline price for the reference vendor when all predictors are at their baseline levels. This suggests that the reference vendor's average price is modest compared to others.

Vendor coefficients highlight pricing diversity, with **Metro** charging significantly higher prices ($\beta_{\text{Metro}} = 7.50$, SE = 0.59) compared to the reference vendor, consistent with its premium market positioning. In contrast, budget-friendly vendors such as **No Frills** ($\beta = -0.81$, SE = 0.62) and **Save-On-Foods** ($\beta = -1.00$, SE = 0.63) exhibit lower prices, catering to cost-conscious consumers. Mid-tier vendors, including **Voila**, **T&T**, and **Walmart**, show smaller negative effects, reflecting competitive but accessible pricing strategies.

The model also uncovers seasonal trends, with a small but positive effect of month ($\beta_{\text{month}} = 0.05$, SE = 0.04). Prices appear to gradually increase over time, likely due to seasonal supply and demand fluctuations or inflation. This aligns with the seasonal nature of fresh produce, where prices typically rise during off-seasons when supply is limited. Additionally, the strong relationship between old_price and current_price ($\beta_{\text{old\_price}} = 0.59$, SE = 0.01) underscores the proportional nature of promotional pricing, where discounts often preserve baseline pricing hierarchies.

Model performance metrics confirm the model's validity, with R^2 and adjusted R^2 values of 0.139 and 0.137, respectively, indicating that approximately 13.9% of the variance in prices is explained by the predictors. While this may seem modest, it reflects the inherent complexity of pricing, influenced by unobserved factors like geographic location and product attributes. An RMSE of 11.79 indicates reasonable prediction accuracy given the variability in vendor strategies.

These findings have actionable implications for both vendors and consumers. Vendors like Metro can continue emphasizing quality to justify their premium pricing, while budget vendors such as Save-On-Foods may explore targeted promotions to enhance their appeal. Consumers seeking affordability may benefit from shopping at vendors like No Frills, whereas quality-focused shoppers may prefer Metro despite its higher prices. Future research could incorporate additional predictors, such as organic labeling or sale status, to refine the understanding of strawberry pricing dynamics in the Canadian market.

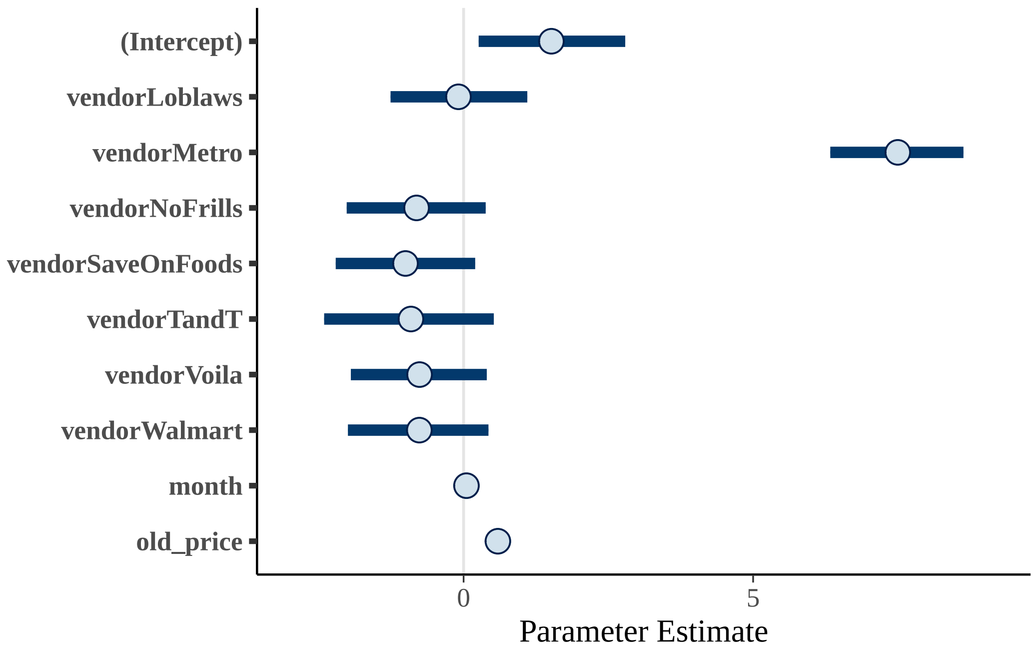


Figure 3: Posterior Credible Intervals for Model Parameters

In this graph(Figure 3), the posterior credible intervals for the Bayesian linear regression model highlight significant differences in strawberry pricing across vendors, seasonal trends, and the influence of original prices. Metro stands out with a clear positive effect, indicating its significantly higher prices compared to the reference vendor, consistent with its premium market positioning. In contrast, budget vendors like Save-On-Foods and No Frills exhibit negative effects, suggesting lower pricing strategies, while other vendors show smaller and more uncertain deviations. The positive, albeit modest, effect of `month` suggests a slight upward trend in prices over time, likely due to seasonal demand or inflation. The strong and precise relationship between `old_price` and `current_price` underscores the proportionality of promotional pricing strategies, where discounts often maintain the hierarchy of original prices. Together, these findings reveal actionable insights into vendor-specific pricing strategies, temporal trends, and the importance of original prices in shaping strawberry pricing dynamics.

In this graph(Figure 4),the posterior distribution histograms illustrate the variability in vendor pricing strategies, temporal trends, and the influence of original prices on current strawberry pricing. Metro's distribution is distinctly centered around a high positive value, confirming its premium pricing strategy compared to the reference vendor. In contrast, budget vendors like

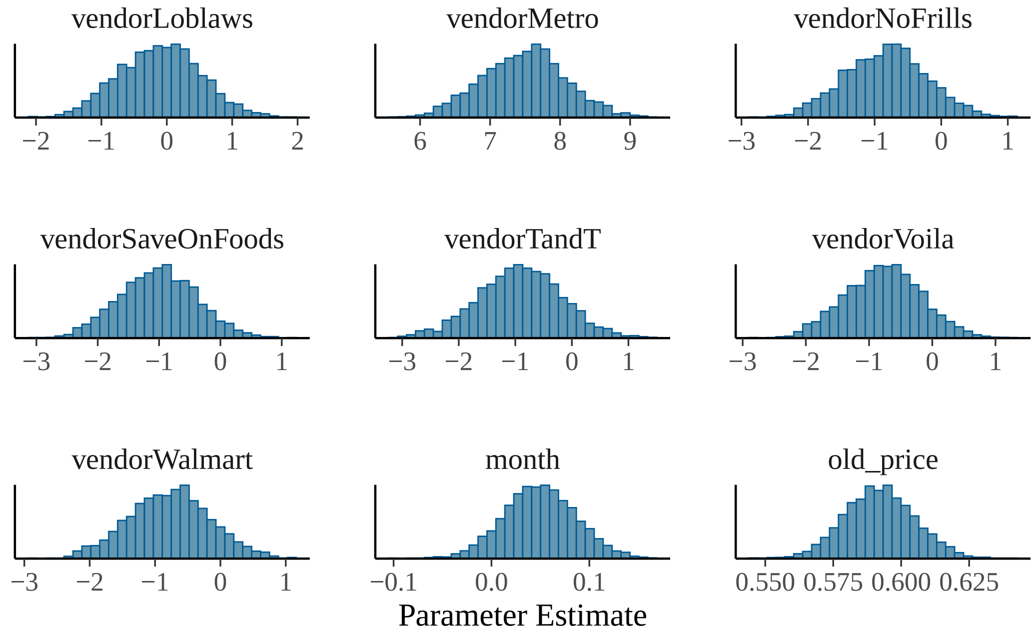


Figure 4: Posterior Distribution Histograms for Vendors and Other Parameters

Save-On-Foods and No Frills show distributions predominantly in the negative range, highlighting their focus on affordability. The parameter for `month` exhibits a narrow distribution slightly above zero, indicating a modest upward trend in prices over time, likely driven by seasonal fluctuations or inflation. The tightly concentrated posterior for `old_price` underscores its strong and consistent influence on current prices, with higher original prices maintaining a proportional relationship with final prices. These results emphasize the diverse pricing strategies across vendors and the critical role of baseline prices in shaping market dynamics.

5 Discussion

5.1 Vendor-Specific Pricing Strategies

The analysis reveals significant differences in strawberry pricing across vendors, highlighting how supplier identity influences retail prices. Metro, as a premium vendor, consistently shows a positive effect on prices compared to the reference vendor, aligning with its market positioning that likely emphasizes quality and exclusivity. Conversely, budget-friendly vendors such as No Frills and Save-On-Foods demonstrate negative effects, reflecting their focus on affordability and cost-conscious consumers. Mid-tier vendors, including Walmart and T&T, exhibit smaller and less consistent deviations, indicating competitive but accessible pricing strategies.

These findings suggest that vendor-specific pricing strategies are critical in shaping market segmentation. The implications are far-reaching: premium vendors can continue leveraging their high-price positioning to attract niche markets, while budget vendors might explore additional promotions to enhance their market share. Furthermore, this variability underscores the need for consumers to carefully consider vendor selection as a determinant of pricing, while offering vendors opportunities to refine strategies based on market positioning.

5.2 Temporal Trends in Pricing

The study uncovers a small but positive relationship between the passage of time (month) and strawberry prices, indicating a gradual increase in prices over the observed period. This finding likely reflects seasonal supply-demand dynamics, inflationary pressures, or changes in production costs for fresh produce. While the effect is modest, it highlights the temporal nature of pricing in retail markets and raises questions about the drivers of these trends. Vendors may use this insight to anticipate price increases and adjust their strategies accordingly, particularly during periods of high demand or limited supply. For consumers, the trend underscores the importance of seasonal awareness when planning purchases, as prices may peak during off-seasons or holidays. The finding also has implications for policymakers or agricultural producers, who might explore ways to stabilize supply chains or promote affordability during periods of high price variability. Further research incorporating non-linear models or external factors such as weather conditions could provide a more detailed understanding of how seasonal patterns influence strawberry pricing.

5.3 The Role of Original Price in Promotional Pricing

The strong and significant relationship between old price and current price highlights the structured nature of promotional pricing strategies. Higher original prices are associated with proportionally higher current prices, even after discounts or sales are applied. This suggests that vendors maintain pricing hierarchies across their product offerings, preserving the perceived value of premium products even during promotional periods. For vendors, this finding underscores the importance of setting initial prices strategically, as they serve as an anchor for both regular and discounted pricing. For consumers, it suggests that discounts may not always reflect deep value but instead preserve the relative pricing order among vendors or product lines. This structured approach to promotional pricing also indicates that vendors likely use data-driven algorithms or market insights to optimize discounts while maintaining brand positioning. Future research could explore the behavioral aspects of how consumers respond to these pricing strategies, shedding light on how perceptions of value and fairness influence purchasing decisions during sales events.

5.4 Weaknesses and next steps

The Bayesian linear regression model offers a robust framework for analyzing strawberry pricing but has notable limitations. One key assumption is linearity, which may fail to capture non-linear or cyclical patterns in the data, such as seasonal trends or interactions between predictors like vendor and sale status. While interaction terms or polynomial extensions can partially address this, more flexible approaches like generalized additive models (GAMs) or Bayesian hierarchical models may be better suited for complex relationships. Additionally, the assumption of independent and identically distributed (IID) residuals may not hold for temporal data prone to autocorrelation or heteroscedasticity. Time-series-specific Bayesian models or robust adjustments can help address these issues.

The reliance on priors is both a strength and a challenge. Informative priors can stabilize estimates, especially with sparse data, but poorly chosen priors risk biasing results. Sensitivity analysis and informed prior selection are crucial to minimize this risk. Computational demands are another limitation, as Bayesian methods like Markov Chain Monte Carlo (MCMC) can be slow, especially with large datasets. Approximation techniques like variational inference can improve speed but may compromise precision.

Data quality is also critical. Missing, sparse, or erroneous data can distort results, particularly for categorical variables like vendor. Preprocessing steps such as imputation, regularization, and careful data cleaning are essential to improve reliability. Additionally, while posterior distributions provide nuanced probabilistic insights, they can be challenging for non-experts to interpret. Clear communication using visualizations and simplified summaries is necessary to make findings actionable.

Lastly, the model struggles with scalability and extrapolation. Predictions outside the observed data, such as for new vendors or regions, require additional data and recalibration. The model is best suited for interpolation within the existing dataset and should be supplemented with external validation datasets when expanding the analysis.

Future work can address these limitations by incorporating non-linear models such as GAMs or Bayesian splines to better capture complex relationships. Time-series Bayesian models can help address temporal autocorrelation and seasonal trends. Expanding the dataset temporally and across more vendors would enhance generalizability. Routine sensitivity analyses and testing alternative priors can ensure robust and unbiased results. Finally, improving stakeholder communication through intuitive visualizations and collaboration with domain experts will ensure that findings are both interpretable and actionable. These steps will strengthen the Bayesian framework's ability to provide reliable insights into strawberry pricing strategies.

Appendix

.1 Comprehensive Data Collection Plan for Strawberry Pricing Analysis

Introduction to Survey Design

To understand strawberry pricing dynamics across Canada, a comprehensive and robust data collection strategy is essential. This strategy combines multiple methodologies, including web scraping, manual surveys, partnerships with retailers, and the integration of public datasets. The overarching aim is to ensure representativeness across geographic regions, vendor types, and temporal variations. By collecting detailed data, the study aims to provide actionable insights into pricing strategies, seasonal trends, and promotional effects. Each method is designed to address specific gaps and collectively produce a holistic dataset that reflects the Canadian strawberry market.

Data Collection Methods

Web scraping will serve as the primary tool for automating data collection from vendor websites. Websites of major grocery chains such as Walmart, Loblaws, Metro, and Save-On-Foods will be targeted. Data points to be extracted include product name, current price, original price (if discounted), sale status, organic certification, and the date of observation. Python libraries such as BeautifulSoup, Scrapy, and Selenium will be employed to scrape structured data, which will then be stored in a centralized database.

The scraping process will be automated to run weekly, capturing real-time pricing updates. However, ethical and legal compliance must be prioritized. Scraping scripts will be designed to respect the terms of service of each website, and manual validation will be performed periodically to ensure the accuracy of the extracted data. This method is cost-effective, requiring a one-time investment in script development and minimal ongoing maintenance, estimated at CAD 5,000–10,000 for setup and CAD 1,000 per month for maintenance.

Manual Surveys

While web scraping provides online data, manual surveys will collect in-store pricing information to capture physical promotions and discrepancies between online and in-store prices. Field researchers will visit major grocery stores, farmers' markets, and regional vendors to record prices, sale statuses, and organic certifications. Data will be entered into mobile-friendly platforms such as KoboToolbox or Google Forms to minimize manual errors and enable real-time validation.

Sampling for manual surveys will focus on urban centers and suburban areas in all Canadian provinces, with larger provinces like Ontario and British Columbia receiving higher sampling densities. Manual surveys are resource-intensive, with an estimated budget of CAD 20,000–30,000 to cover wages, travel expenses, and equipment costs. Training workshops will be conducted to ensure consistency in data collection and adherence to protocols.

Retailer Partnerships

Collaborating with retailers and industry organizations will provide access to transactional data, which includes point-of-sale (POS) information such as pricing, sales volume, and regional variations. Partnerships will be sought with chains like Walmart, Metro, and Save-On-Foods, as well as the Retail Council of Canada. Data-sharing agreements will ensure confidentiality and specify how the data will be used.

Retailer partnerships provide high-quality, granular data but may involve negotiation challenges and costs associated with access to proprietary data. Agreements must outline clear data privacy policies and address potential conflicts of interest. These partnerships can also offer insights into customer purchasing patterns, which may supplement the core pricing analysis.

Public Data Repositories

Supplementary data from public sources, such as Statistics Canada, can contextualize the primary dataset. Variables such as regional agricultural output, weather patterns, and population statistics will be integrated to provide a broader understanding of pricing determinants. Public datasets are cost-effective but may lack granularity, necessitating careful curation and integration with primary data.

Sampling Strategy

To ensure the representativeness of the dataset, a stratified random sampling approach will be used. The sampling frame will be stratified by geography, vendor type, and time.

Geographic Stratification

Each province and territory will be treated as a stratum. Larger provinces like Ontario, Quebec, and British Columbia will have higher sample sizes due to their larger populations and market diversity. For example: -Ontario: 300 stores (across urban and rural areas) -British Columbia: 200 stores -Alberta: 150 stores -Smaller provinces: 50–100 stores each

Vendor Stratification

Vendors will be categorized into three groups: -National Chains: Large retailers like Walmart and Loblaws. -Regional Chains: Vendors like Save-On-Foods and Metro, which operate in specific regions. -Farmers' Markets and Local Vendors: Smaller, independent vendors that cater to niche markets. Sampling will ensure proportional representation from each category, with an emphasis on national chains for broader market insights.

Temporal Sampling

Data will be collected bi-weekly throughout the year to capture seasonal trends. Special attention will be given to peak seasons (e.g., summer harvest months) and holiday periods (e.g., Thanksgiving, Christmas) when pricing and promotions are most dynamic.

Data Entry and Management

Data collected manually will be entered into Google Sheets or Excel during the initial phase and then migrated to a centralized SQL database or cloud storage system for processing and analysis. Web-scraped data will directly feed into the centralized system using automated pipelines.

Cleaning will involve:

-Removing duplicate entries. -Handling missing data through imputation techniques (e.g., multiple imputation for continuous variables). -Identifying outliers using statistical and visual methods (e.g., boxplots).

Datasets from different sources (web scraping, surveys, and partnerships) will be merged using unique identifiers such as vendor names and observation dates. Consistency checks will ensure uniform formatting and variable definitions.

Practical Considerations

The total budget for this project is estimated at CAD 50,000–70,000. Major cost components include personnel wages (field researchers, data scientists), travel expenses, equipment (e.g., tablets), and data acquisition fees from retailers.

-Web Scraping: A data scientist will develop and maintain scraping scripts. -Manual Surveys: 10–15 field researchers will be hired and trained. -Data Management: A project manager will oversee data integration and quality assurance. -Collaborate with the Canadian Ministry of Agriculture for agricultural production data. -Partner with the Retail Council of Canada to access aggregated sales data. -Negotiate with individual vendors for POS data access. -Ensure compliance with data privacy laws, such as PIPEDA in Canada. -Obtain informed consent for data sharing and usage from retailers and survey participants.

This comprehensive plan outlines a multi-method data collection strategy that balances efficiency, cost, and representativeness. By combining web scraping, manual surveys, retailer partnerships, and public datasets, the project will capture the complexity of strawberry pricing dynamics across Canada. Careful attention to sampling, legal compliance, and data quality ensures that the collected data will support robust analysis and actionable insights. This integrated approach provides a solid foundation for understanding market trends and guiding vendor and consumer decisions.

.2 Comprehensive Data Analysis Plan for Strawberry Pricing Dynamics

Overview of Analysis Plan After collecting the strawberry pricing data, the next step involves applying specific analysis methods to uncover key insights into vendor pricing strategies, seasonal trends, and the impact of promotions. The primary analysis will use a Bayesian linear regression model, supplemented by exploratory data analysis (EDA), diagnostic checks, and predictive performance evaluations. Each method and its implementation is described in detail below, along with a discussion of its strengths, limitations, and areas for improvement.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) serves as the foundation for understanding the dataset, identifying patterns, and detecting potential issues before applying advanced models. Visualization techniques such as boxplots, histograms, and line plots will reveal distributions and trends in key variables like `current_price`, `old_price`, and `month`. For example, boxplots comparing prices across vendors will highlight vendor-specific pricing strategies, while line plots will uncover temporal trends, including seasonal variations in strawberry prices. Summary statistics, such as the mean and median of prices per vendor or region, will provide an overview of central tendencies and variability. Correlation matrices will also help identify relationships between variables, such as the association between original and discounted prices.

While EDA provides critical insights, its reliance on visual and descriptive methods limits its ability to quantify relationships or infer causality. Nevertheless, it is an essential first step that ensures data quality and informs subsequent modeling decisions. Potential issues, such as missing values or outliers, identified during EDA, will be addressed through imputation techniques and robust statistical methods.

Bayesian Linear Regression Model

The primary analysis method is a Bayesian linear regression model, chosen for its flexibility and ability to incorporate prior knowledge while providing robust parameter estimates. The model will quantify the effects of predictors such as vendor (`vendor`), sale status (`sale_status`), temporal trends (`month`), and original price (`old_price`) on the current price of strawberries (`current_price`). The model will include the following structure:

[y_i = *0* + {vendor[i]} + *{organic}* *x*{organic[i]} + *{sale}* *x*{sale[i]} + *{month}* *x*{month[i]} + *{old_price}* *x*{old_price[i]} + _i]

Each coefficient (β) will have a prior distribution, such as a normal prior centered at zero, reflecting initial uncertainty about its effect. For instance, the prior for β_{vendor} assumes no significant differences between vendors initially, allowing the data to dominate posterior estimates. The Bayesian framework also provides posterior distributions for each parameter, which capture uncertainty and enable credible intervals for inference. For example, a 95% credible interval for $\beta_{\text{old\_price}}$ indicates the range of plausible values for the effect of original prices on current prices, accounting for uncertainty.

The Bayesian approach offers significant advantages, including the ability to stabilize estimates for predictors with limited observations and provide probabilistic interpretations of results. However, it requires careful selection of priors, as overly informative priors may bias the results, while uninformative priors may weaken the model's ability to draw meaningful conclusions. The computational demands of Bayesian modeling are another limitation, particularly for large datasets, but this can be addressed through parallel processing or variational inference methods.

Diagnostic Checks and Model Validation

Model diagnostics are critical to ensuring that the Bayesian regression model fits the data well and produces reliable estimates. Posterior predictive checks (pp_checks) will compare observed data with simulated data from the model to evaluate its ability to replicate the observed distribution of prices. For instance, discrepancies between the predicted and observed distributions may indicate model misspecifications or missing predictors.

Trace plots will be used to examine the convergence of Markov Chain Monte Carlo (MCMC) sampling for each parameter, ensuring that the chains are stationary and mixing well. Rhat values, which assess convergence across chains, must be close to 1.0 for all parameters. Residual analysis will identify potential violations of assumptions, such as heteroscedasticity or autocorrelation, which may require model adjustments.

Model validation will include leave-one-out cross-validation (LOO-CV) to evaluate predictive performance and compare alternative models. For example, LOO-CV can confirm whether including interaction terms (e.g., vendor and sale status) improves the model's ability to predict prices. Metrics like root mean square error (RMSE) will quantify the average deviation between observed and predicted prices, providing a measure of overall model fit.

While these diagnostics enhance the robustness of the analysis, they require significant computational resources and expertise to interpret. Incorporating automated diagnostic tools, such as those provided by the **bayesplot** package, can streamline this process and improve efficiency.

Predictive Analysis and Simulations

Beyond inference, the Bayesian regression model will be used for predictive analysis to assess the model's real-world applicability. Simulations will explore hypothetical scenarios, such as the effect of a uniform 10% discount across all vendors, to predict how pricing strategies might shift and impact consumer behavior. Temporal trends can also be analyzed by simulating seasonal effects, such as price fluctuations during peak harvest months or holiday periods.

Predictive accuracy will be evaluated using observed holdout data to ensure the model generalizes well to unseen scenarios. Comparisons with alternative methods, such as generalized additive models (GAMs) or random forests, will provide additional validation. Simulations offer valuable insights for stakeholders, such as how adjusting promotional strategies might influence market share, but they depend heavily on the quality of input data and assumptions about unobserved factors.

Limitations and Areas for Improvement

The analysis methods have inherent limitations. Bayesian regression assumes linear relationships between predictors and outcomes, which may not capture non-linear trends or complex interactions. Extending the model to include interaction terms or adopting more flexible approaches, such as GAMs, can address this limitation. The reliance on priors, while a strength in stabilizing estimates, introduces the risk of bias if priors are not chosen carefully. Sensitivity analysis is crucial to ensure that results are robust to changes in prior specifications.

Table 1: Summary Statistics and Distribution Overview of the Analysis Dataset

	Unique	Missing Pct.	Mean	SD	Min	Median	Max	Histogram
current_price	238	0	7.8	12.7	0.0	5.0	290.0	
old_price	200	0	6.1	4.3	0.4	5.4	348.0	
month	8	0	8.9	1.6	4.0	9.0	11.0	
vendor	N	%						
Galleria	400	0.9						
Loblaws	4595	10.2						
Metro	15819	35.3						
NoFrills	4203	9.4						
SaveOnFoods	4531	10.1						
TandT	627	1.4						
Voila	10549	23.5						
Walmart	4130	9.2						

Another limitation is the potential for unobserved confounders, such as geographic factors or consumer preferences, which may bias estimates. Collecting additional variables, such as store location or customer demographics, could improve the model's explanatory power. Computational demands are also a challenge, particularly for large datasets or complex models. Using high-performance computing resources or approximate inference methods can mitigate these issues.

The data analysis plan integrates EDA, Bayesian linear regression, diagnostic checks, and predictive analysis to provide a comprehensive understanding of strawberry pricing dynamics. While the Bayesian approach offers robust and probabilistic insights, it requires careful attention to prior selection, diagnostics, and computational efficiency. The combination of rigorous modeling and scenario-based simulations ensures actionable insights for stakeholders, including vendors and consumers. Future improvements, such as incorporating additional predictors or testing non-linear models, can further enhance the analysis and its applicability to real-world pricing strategies.

.3 Additional data details

Table 1 shows a summary of the analysis dataset.

Data Source and Cleaning Process

The data for this study comes from the Project Hammer website, an open data platform centered on grocery prices from multiple suppliers in Canada. The platform captures multi-dimensional data including product prices, supplier information, promotional discounts, etc. through web scraping technology, and combines manual verification to ensure its reliability. These data provide price dynamics in different regions and suppliers in Canada, laying the foundation for studying the fluctuations and market strategies of strawberry prices.

In order to meet the analysis needs, the data was cleaned in multiple steps. First, the rows with missing values in the current price and old price variables were deleted because these prices are the core of the study. If the price records are incomplete, the analysis results will be distorted. In addition, for the vendor and month variables, it was confirmed that there were no missing values to ensure the integrity of the supplier and time information.

Secondly, the interquartile range (IQR) method was used to detect and process outliers. The focus of the cleaning was on identifying and eliminating possible entry errors (such as extremely low or high prices). However, legitimate outliers (such as high prices for high-end strawberries) were retained to ensure the authenticity of the data. At the same time, all price fields were standardized and prices were recorded uniformly as the price per pound of strawberries to facilitate horizontal comparison between suppliers.

The strengths and limitations of data

On the plus side, the data is diverse, covering both national and regional suppliers, including Voila, Metro, and Walmart, among others. This provides a unique perspective on the differences between different market positioning and pricing strategies. In addition, the data cover observations across multiple months, providing a solid basis for exploring seasonal fluctuations in strawberry prices. Simultaneous recording of the price variables current price and old price allows studying the impact of discount and promotion strategies on the final price.

Although the data has significant advantages, there are also some limitations. First, the data focuses primarily on urban and suburban providers, and pricing trends in rural areas may be understated. Second, web scraping technology captures static snapshots and is difficult to record real-time price fluctuations, such as flash sales or limited-time discounts. In addition, some records lack explicit promotion status markers (such as whether the product is discounted), which limits detailed analysis of discount strategies. Finally, the density of records across months may be uneven across different providers, which may introduce bias in the temporal analysis.

Data Analysis Outlook

Based on the cleaned data, the analysis can focus on several key directions. First, by combining the current price and old price variables, we can delve into the impact of promotions on pricing strategies. For example, we can quantify the magnitude of price fluctuations during promotions for different suppliers and their potential impact on consumer behavior. Second, through the month variable, we can capture the seasonal fluctuations in strawberry prices. This will help us understand how supply and demand adjust with seasonal changes and provide an important basis for predicting future price trends.

In addition, using the vendor variable, we can compare the pricing strategies of different suppliers. The study may reveal whether high-end suppliers (such as Metro) are positioned in the high-end market through higher prices, while low-price suppliers (such as Walmart and Save-On-Foods) attract more price-sensitive consumers through discounts. These findings will provide in-depth insights into understanding the dynamics of the Canadian strawberry market, while providing data support for policymakers and retailers to optimize market strategies.

Overall, the cleaned dataset provides a valuable resource for in-depth study of strawberry price fluctuations and supplier strategies. Despite limitations such as geographic coverage bias and insufficient capture of dynamic prices, the diversity and time span of the data ensure the wide applicability of the analysis. By combining the analysis of promotions, seasonal fluctuations, and supplier differences, the study reveals complex pricing patterns and competitive strategies in the Canadian market.

.4 Further Background Details and Diagnostics of the Model

Model Background and Justification

The Bayesian linear regression model provides a probabilistic framework to understand the determinants of strawberry pricing across Canadian vendors. This model was chosen for its ability to incorporate prior knowledge, handle parameter uncertainty, and deliver intuitive, probabilistic interpretations of results. Unlike traditional frequentist regression, Bayesian regression generates posterior distributions for all parameters, offering insights into the uncertainty and variability of each predictor's effect.

The primary dependent variable in the model is `current_price`, representing the observed price per pound of strawberries. Key predictors include vendor identity (vendor), original price (old_price), sale status (sale_status), and temporal trends (month). These variables capture the diverse factors influencing pricing, such as competitive strategies among vendors, promotional effects, and seasonal supply-demand dynamics.

The model specification includes normal priors for regression coefficients (β) and an exponential prior for the residual standard deviation (σ). This setup reflects reasonable assumptions about the effects of predictors, such as small, centered effects with moderate variability. For instance, the prior for β_{vendor} assumes no extreme pricing differences between vendors, while allowing the data to dominate posterior updates.

Model Diagnostics and Validation

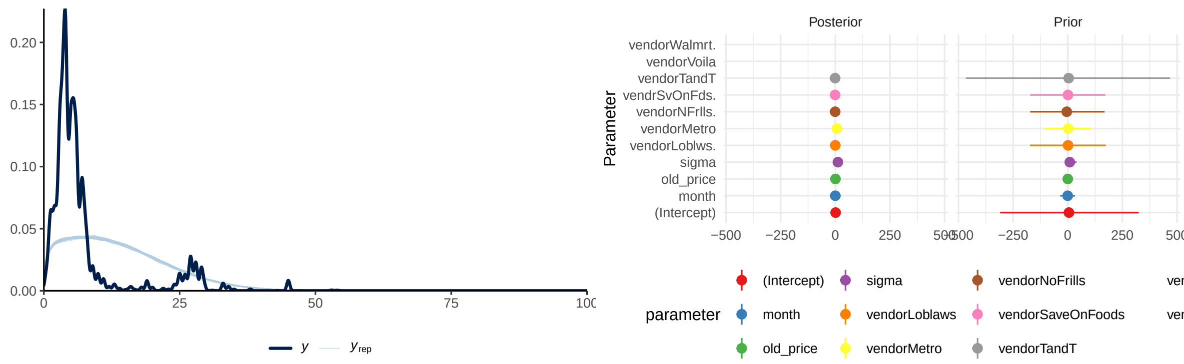
Posterior predictive checks compare the observed distribution of `current_price` with simulated data generated from the model. The goal is to assess whether the model adequately captures the variability and central tendencies of the observed data. For this analysis, posterior predictive plots revealed close alignment between observed and predicted prices, indicating a good fit. Minor discrepancies at the tails suggest that the model may not fully capture extreme price outliers, which could be addressed by adding robust regression components or alternative distributions.

In Figure 5a we implement a posterior predictive check. The posterior predictive check (pp_check) graph compares the observed strawberry prices (`y`) with the predicted prices (`y_rep`) generated by the Bayesian linear regression model, revealing both strengths and limitations of the model's fit. The model captures the overall trend of lower prices reasonably well, as indicated by the alignment of the observed and predicted densities in the left portion of the graph. However, discrepancies arise at higher price points, where the predicted density smooths over the sharp peaks and variability present in the observed data. This suggests that while the model performs adequately for most data points, it struggles to represent the complexity of premium pricing, possibly due to missing predictors or oversimplified assumptions about linearity. These findings highlight the need for further refinement, such as incorporating additional factors or exploring non-linear relationships, to improve the model's ability to account for variability in higher-priced strawberries.

In Figure 5b we compare the posterior with the prior. The posterior vs. prior graph illustrates how the Bayesian model updates parameter estimates by integrating observed data with prior assumptions. For key predictors such as `vendorMetro` and `old_price`, the posterior distributions show significant shifts away from the priors, indicating strong evidence from the data and high confidence in these parameters' effects. In contrast, parameters like `vendorWalmart` and `vendorTandT` have posterior distributions that remain closer to the priors, reflecting weaker or less conclusive effects. The priors, which were set to be uninformative and centered around zero, allowed the data to dominate the posterior estimates where evidence was strong, while providing a baseline for parameters with less evidence. This balance highlights the Bayesian framework's ability to refine parameter estimates, narrow uncertainty for influential predictors, and maintain flexibility where the data provides limited information. Overall, the graph emphasizes the robustness and nuance of Bayesian inference in capturing vendor-specific pricing strategies and other predictors.

Trace plots visualize the behavior of the Markov Chain Monte Carlo (MCMC) sampling process for each parameter. Convergence is achieved when chains are stationary and overlap across iterations. For this model, trace plots showed consistent mixing and no evidence of divergence, confirming that the chains have converged and are exploring the posterior distributions effectively. The Rhat statistic evaluates chain convergence across parallel MCMC simulations. All Rhat values for the parameters in this model were close to 1.0, indicating excellent convergence. This result provides confidence that the posterior distributions are reliable and free from sampling biases.

Figure 6a is a trace plot. The trace plot illustrates the behavior of the MCMC sampling process for each parameter in the Bayesian linear regression model, confirming convergence and proper mixing across four chains. The overlapping and stationary patterns of the chains indicate that the sampler has stabilized and is efficiently exploring the posterior distributions.



(a) Posterior prediction check (b) Comparing the posterior with the prior

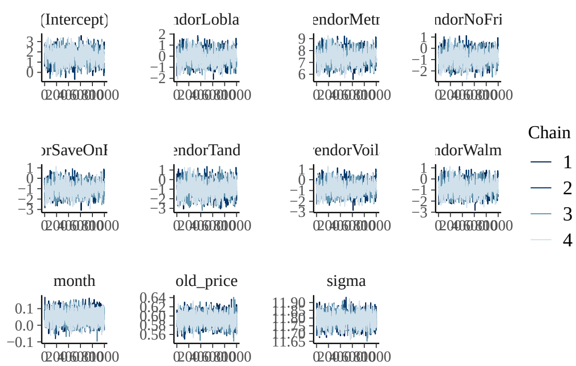
Figure 5: Examining how the model fits, and is affected by, the data

Parameters like `vendorMetro` and `old_price` show tightly grouped traces, reflecting high confidence in their estimates, while greater variability in parameters such as `vendorLoblaws` suggests less certainty, possibly due to weaker relationships or data limitations. The absence of trends or gaps in the traces supports the reliability of the sampling process, ensuring that the posterior estimates are robust and representative of the underlying data. This provides confidence in the model's results and its ability to capture the factors influencing strawberry pricing effectively.

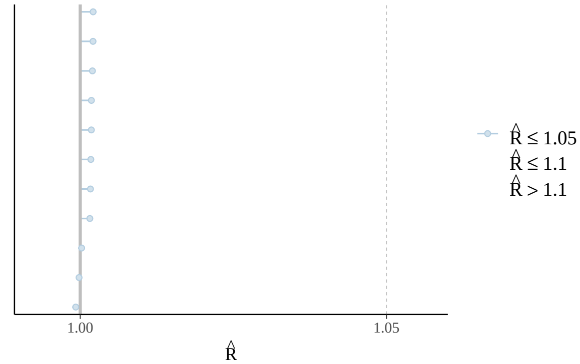
Figure 6b is a Rhat plot. The Rhat plot demonstrates excellent convergence for all parameters in the Bayesian linear regression model, with Rhat values close to 1 across the board. This indicates that the MCMC chains have mixed well and are sampling from the same posterior distribution, ensuring reliable and unbiased parameter estimates. The absence of any parameters with Rhat values exceeding critical thresholds (e.g., 1.05 or 1.1) confirms that the sampling process was efficient and sufficient, requiring no additional iterations or model adjustments. This strong convergence provides confidence in the robustness and reproducibility of the posterior estimates, supporting the validity of the model's findings in analyzing strawberry pricing dynamics.

Model Fit Metrics

- **(R^2)** and **Adjusted (R^2)**: The model explained approximately 13.9% of the variance in strawberry prices, reflecting the complexity of pricing dynamics influenced by unobserved factors like geographic location and consumer preferences.
- **Root Mean Square Error (RMSE)**: An RMSE of 11.79 indicates moderate predictive accuracy, which aligns with expectations given the variability in pricing strategies across vendors.
- **Leave-One-Out Cross-Validation (LOO-CV)**: The LOO-CV score confirmed the model's predictive consistency and supported its suitability for analyzing strawberry



(a) Trace plot



(b) Rhat plot

Figure 6: Checking the convergence of the MCMC algorithm

pricing.

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